calce™ Prognostics

NRA Progress Report

# Reliable Diagnostics and Prognostics for Critical Avionic Systems

# 07-IVHM1-07-0042

Center for Advanced Life Cycle Engineering (CALCE)
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# Project Objectives

- Increase aircraft safety and reduce aircraft maintenance costs by improving the accuracy of fault determination in critical avionics systems.
- Develop approaches to detect faults, to model degradations, and to predict failures in avionics components.
- Develop a methodology involving parameter selection, feature extraction, pattern recognition, anomaly detection, parameter isolation, and remaining useful life estimation.
- Equip NASA with the ability to monitor the health of onboard electronics of an aircraft in actual operating conditions to increase the safety and availability of the aircraft.

# Deliverables

| Deliverables | Completion Date |
|---|---|
| **Initial system description and documentation** | **09/30/2008** |
| **Nominal / faulty data sets for initial system** | **09/30/2008** |
| **Prognostic algorithm software implementation and documentation** | **09/30/2009** |
| Demonstration of prognostic algorithms running online with initial data sets | 09/30/2009 |
| Evaluation of performance of prognostic algorithms running with initial data sets | 09/30/2009 |
| Acceptability determination of supplied aircraft avionics data | 01/01/2010 |
| Demonstration of one of the following:<br>Prognostic algorithms running online with supplied aircraft avionics data and evaluation of their performance<br>Diagnostic algorithms running online with initial system data | 09/30/2010 |
| At least one published conference paper or journal article describing the work performed | 09/30/2010 |
| Final report | 09/30/2010 |

# Test Vehicle

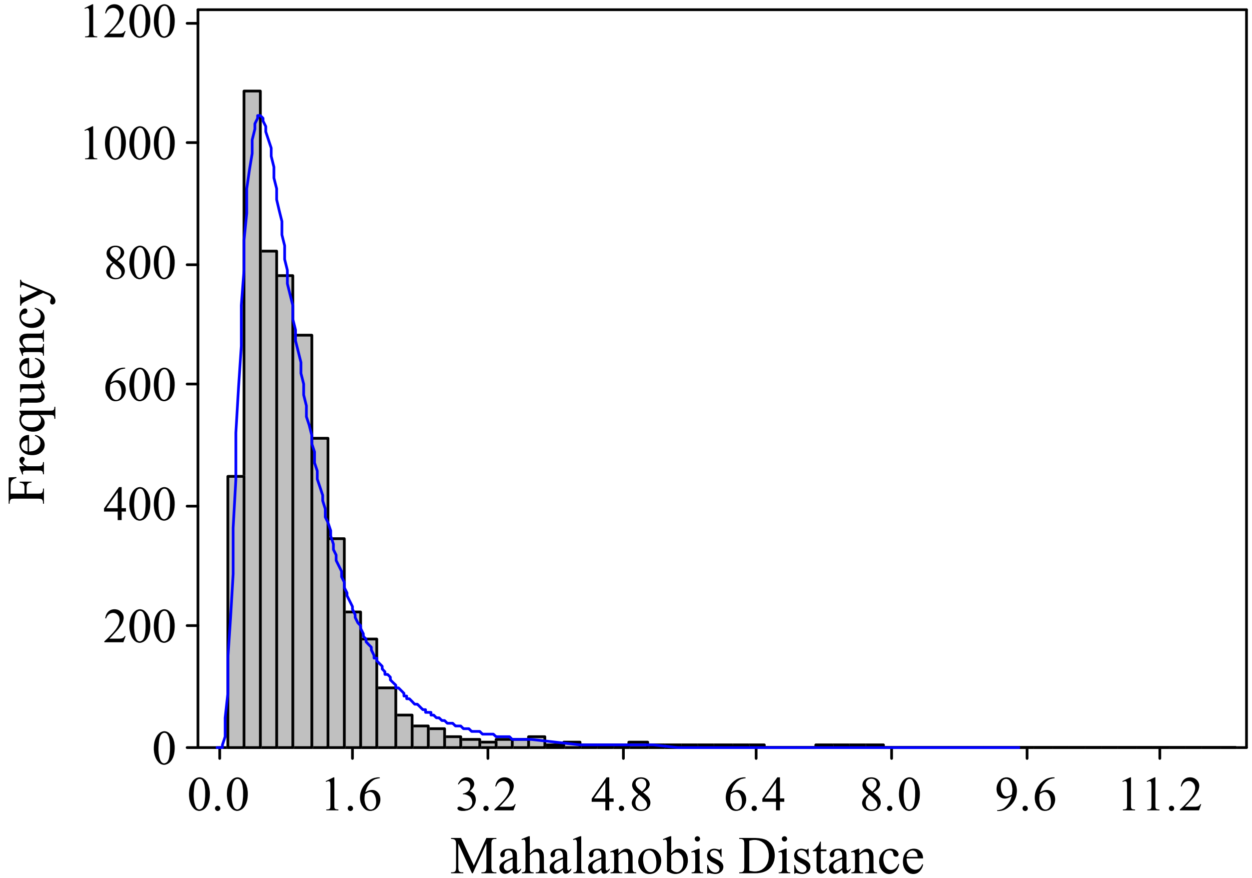
- Avionics systems have components and architecture that are similar to computer systems:
  - Microprocessors
  - FPGAs
  - Memory systems
  - Power systems
  - Operating systems
  - Firmware
- Computers are complex electronics systems that can be used as a test vehicle for developing robust prognostics methodologies.
- The prognostic methodologies tested and validated for computers can be implemented for critical avionics systems.
- CALCE is working with computer companies and can leverage these companies' data and product knowledge for prognostics research.

# Data for Developing Prognostic Methods

- A product's health is the general state of the product with respect to the expected normal operating condition.
- A healthy baseline can be formed by collecting data at the beginning of a system's operational life or using data collected before encountering any fault.
- 10 new computers were tested under 72 different combinations of environmental, power, and usage conditions.
- Specific system parameters for each computer were monitored including fan speed, main component temperature, resource management parameters, etc.
- A baseline data set was generated from the above 10 computers to train the algorithms used in this research.
- Sample test data was taken from field returned computers

# Sample Representation of “Healthy” Data

Mahalanobis Distance, a feature of healthy training data.




Various detection and inference techniques can be used (i.e., Hypothesis testing, Bayesian classification, etc.) if the data can be represented by a parametric distribution.

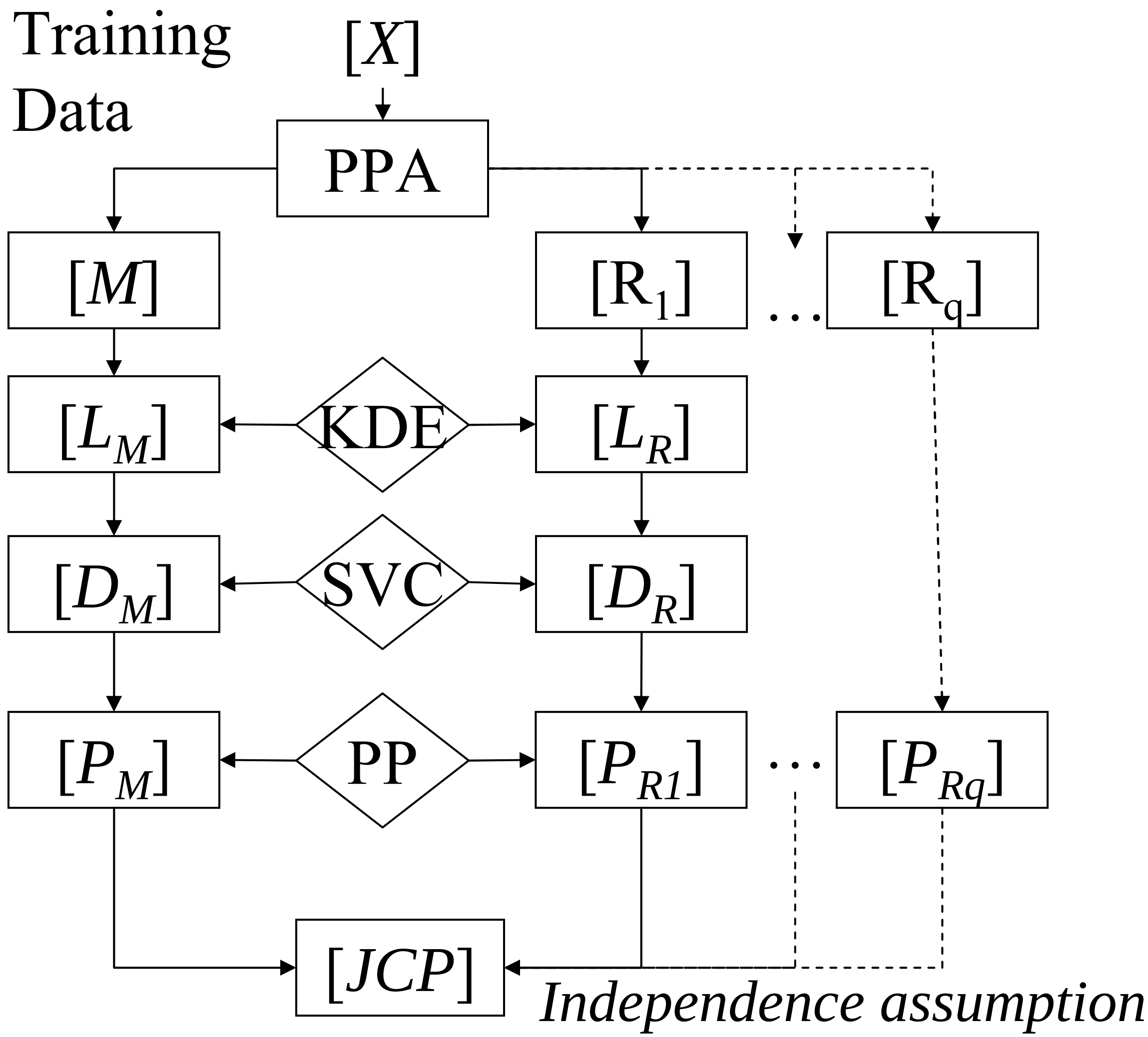
# Algorithms

# Algorithms for Anomaly Detection

- Bayesian Support Vector Machine (BSVM) based approach
  - In the absence of negative class data (fault or failure information), a one-class-classification approach is used to determine healthy and unhealthy class data from training data.
  - ❖ Projection Pursuit Analysis (PPA) based approach
    - Data are projected onto principle component and residual spaces, and statistics, including $T^2$ and SPE, are computed for training data.
- Symbolic Time Series Analysis (STSA) based approach
  - Training data is used to model a healthy system by partitioning its derived performance measure in space and time.
  - ❖ Mahalanobis Distance (MD) based approach
    - A baseline for the normal operation of these computers is created, including the distribution of performance parameters, the MD of training data, and ΔMD distribution of performance parameters.

# Anomaly Detection Approach Using BSVM

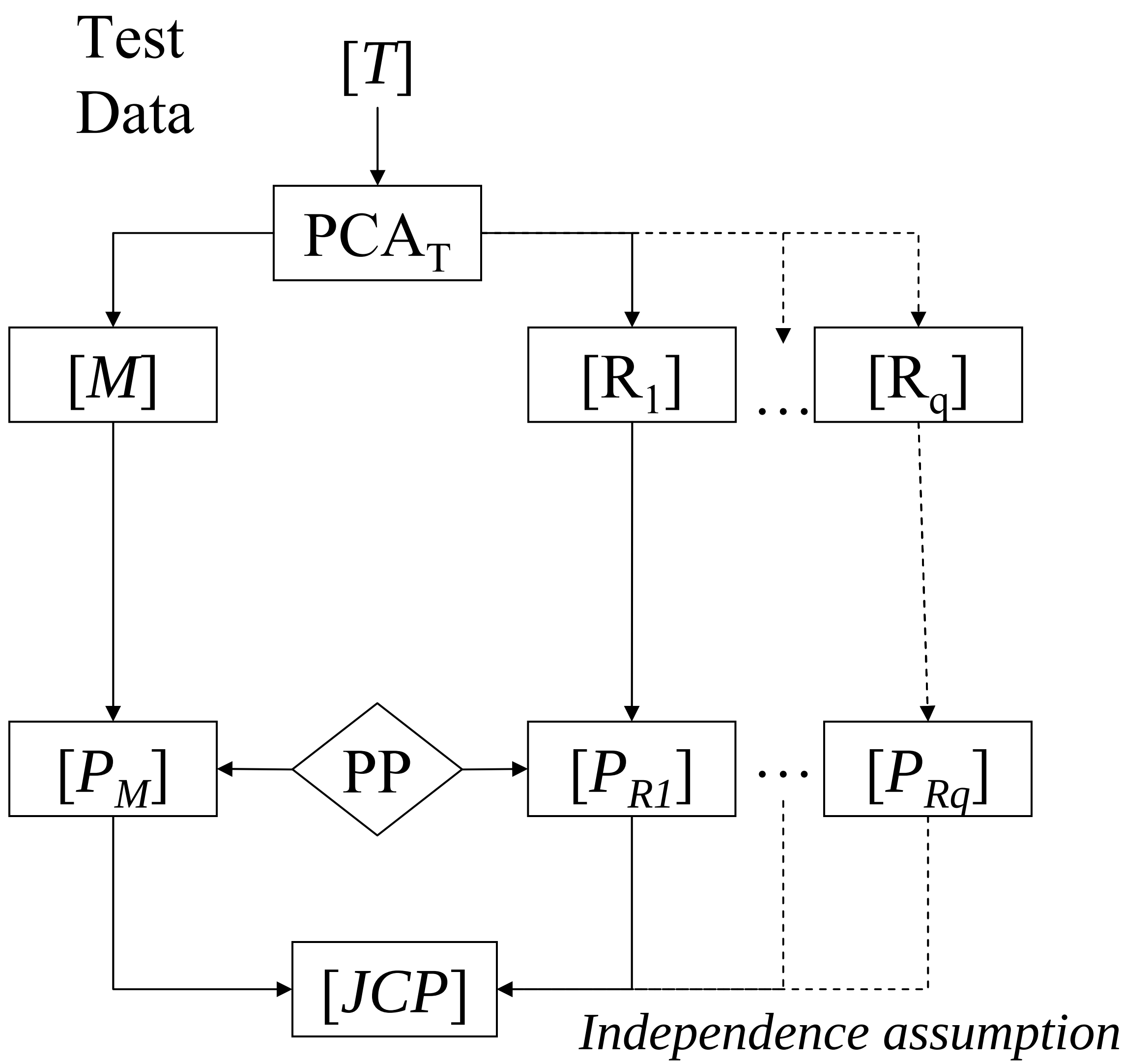
- Decompose into lower dimensional models.
- Compute density of training data to estimate negative class.
- Construct an optimal classifier function D.
- Compute the posterior class probabilities (PP).
- Compute the joint posterior class probabilities (JCP).




KDE: Kernel Density Estimation, SVC: Support Vector Classifier

# Anomaly Detection Approach using BSVM

- Project onto lower dimensional models.
- Compute the posterior class probabilities (PP).
- Compute the joint posterior class probabilities (JCP).




PCA$_T$: projection of test data based on covariance of training data

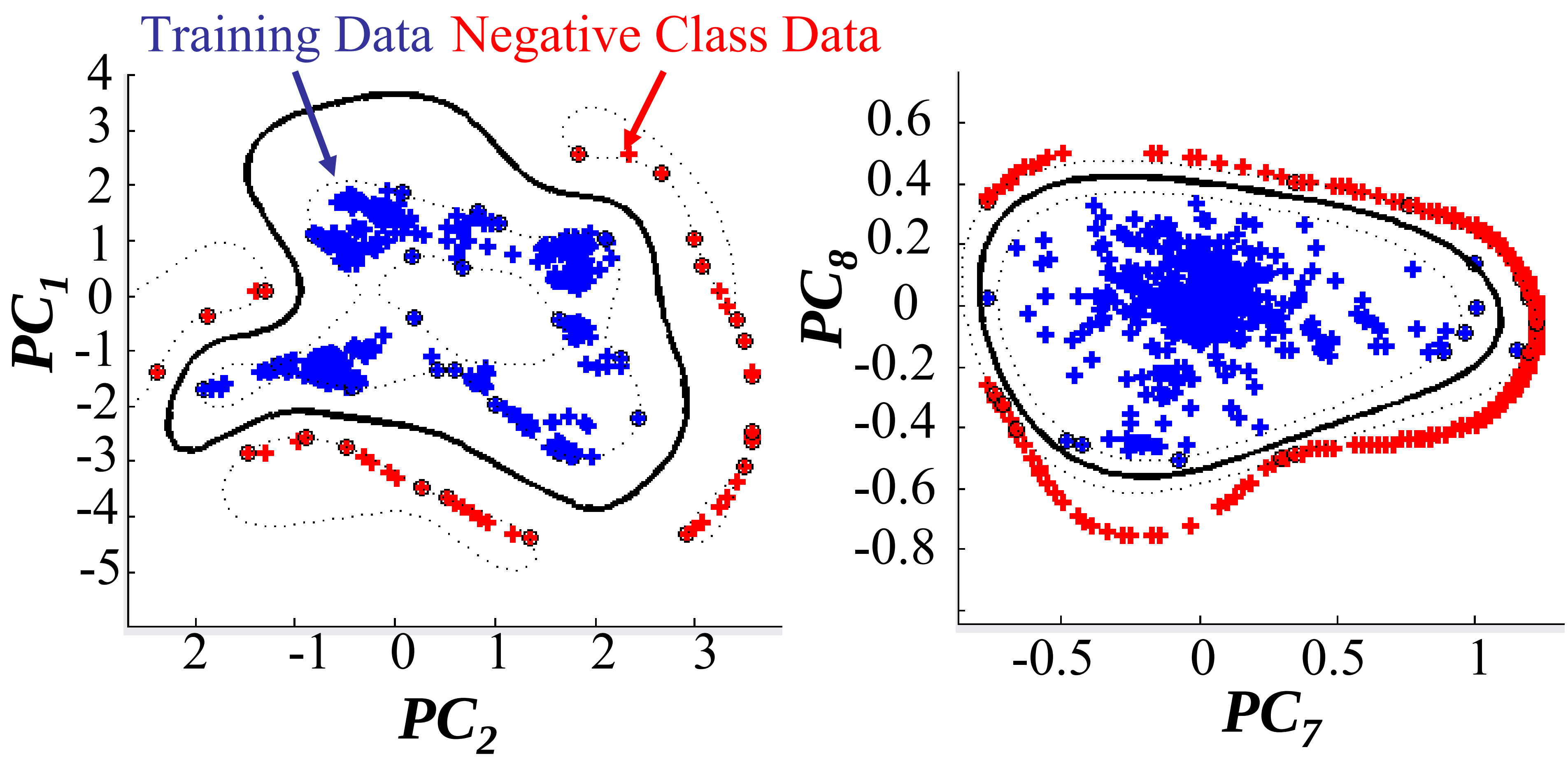
# Evaluation of Test Computer Using a BSVM

- The training – small % amount of baseline data.
- Sample test data – 5000 sample points.
- Two 2-dimensional subspace decompositions were used:
  - Model subspace, *explained variance: ~0.62*
  - Residual Subspace, *explained variance: ~0.12*
- BSVM results identifies system abnormal behavior that coincides with the operation of the computer fan.

# BSVM Classifiers

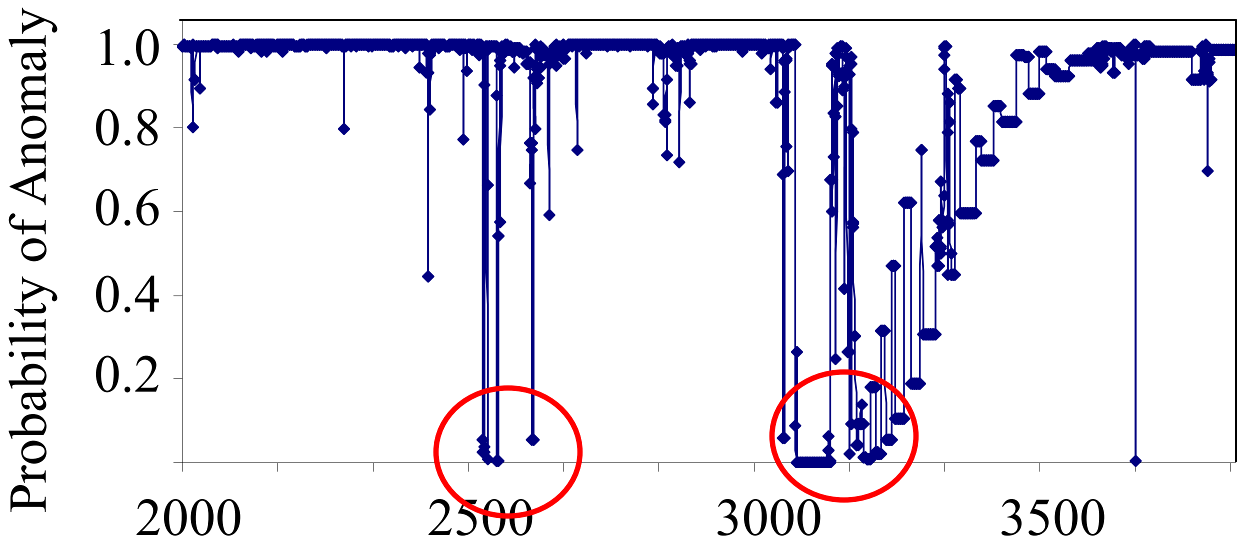
## Model Space

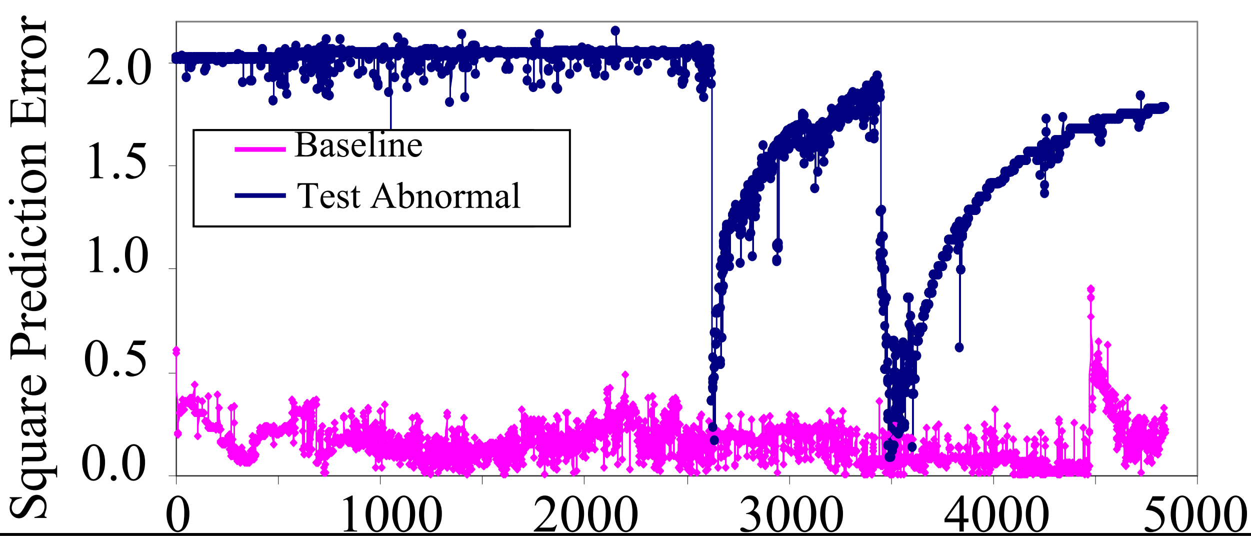
## Residual Space




*PC* – principal component

# BSVM Application on Field - Returned Test Computer



# Anomaly Detection Approach Using STSA

Monitor Parameters

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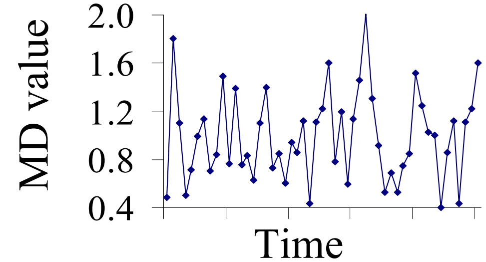
Construct MD time series

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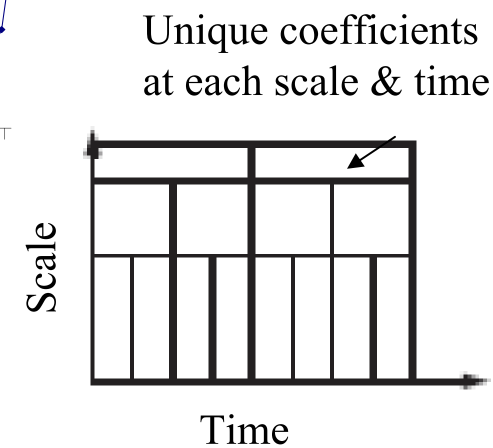
Apply wavelet transform

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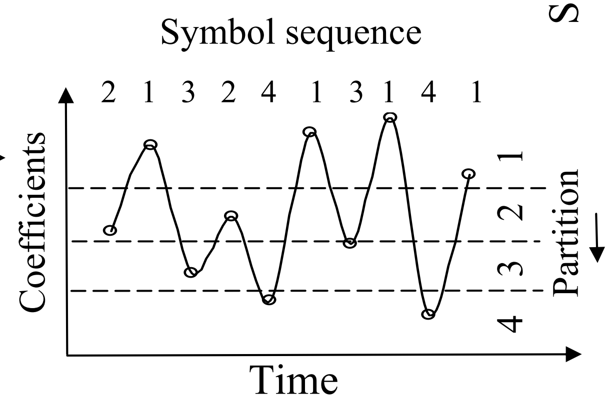
Create symbolic time series

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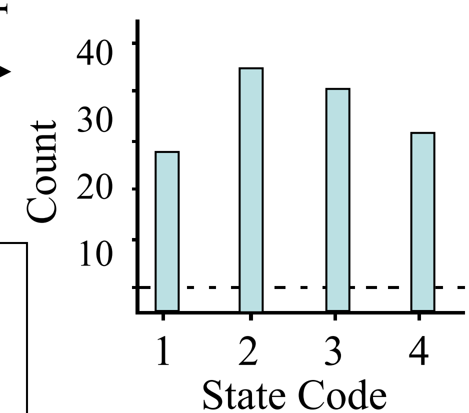
Generate Markov state model

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Calculate prognostic measures

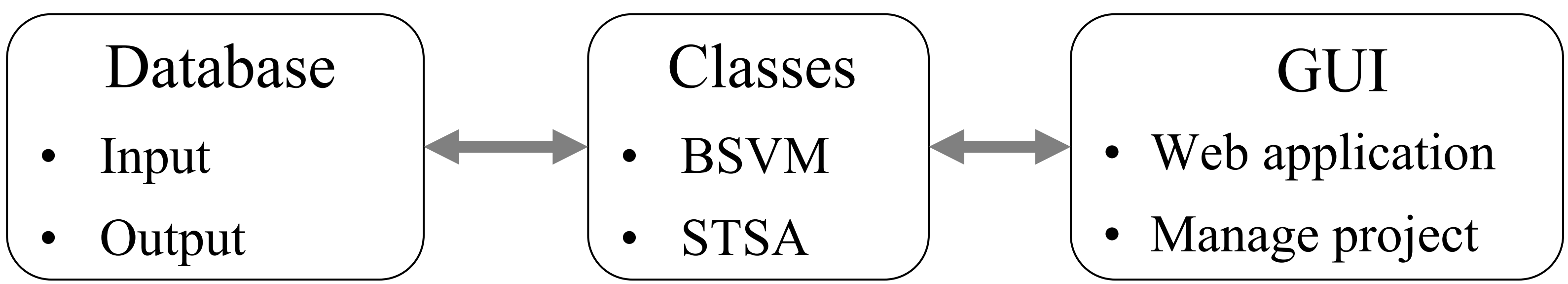
- Identification of new state
- Change in transition prob.
- Time to reach a state

# STSA Application on Field-Returned Test Computer

| | |
|---|---|
| Number of training states 110 Vs. Number of test states 118 | 8 |
| Change in critical transition probability, training Vs. test | $\pi_{0}-\pi_{T}$ = 0.0443 |
| Change in mean time to stay in critical state | $T_0 - T_T = 60$ units |

# Software Development

- Software is being developed for diagnostics and prognostics by implementing Symbolic Time Series Analysis (STSA) and Bayesian Support Vector Machine (BSVM) analysis
- The software stores output in an SQL database.
- Classes are written in C#.



# Summary

- A computer system has been identified as a demonstration vehicle for PHM algorithm development.
- Training data to represent healthy system have been collected.
- Approaches for anomaly detection that are being developed include BSVM and STSA.
- Actual data from computers are used to demonstrate detection capability of the BSVM and STSA approaches.
- Software is being developed for all the approaches discussed.

# Next Steps

- Continue to run experiments to generate and record soft faults and intermittent failures. (In-progress)
- Detect the intermittent events using following algorithms:
  - Symbolic Time Series Analysis (STSA)
  - Bayesian Support Vector Machines (BSVM)
- Incorporate all approaches into a software.